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On selection and combination of relevant color components for edge detection

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Abstract

This paper aims to define the best suited combination of color components for edge detection. This is done by a selection of the most relevant components from each color space. First, we compare the performances of the conventional canny edge detector applied to this color spaces. Then, we tend to assess the accuracy of detected edges by using two quantitative methods namely, Fram and Deutsch in addition to robust statistical error measures. Experiments have been conducted on images from BSDS300 database using perceptual and correlated color spaces. We additionally perform these experiments on a progressively contaminated versions of each processed image. Relevant color components are defined according to their detection accuracy and gaussian noise robustness. The obtained results show that Y(luma of YIQ), Y(luminance of $YCbCr$) and V(brightness of HSV) perceptual color components remains the best candidates for an eventual combination.

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Keywords: Color Spaces; Edge Detection; Quantitative Evaluation.

1. INTRODUCTION

Edge is an important image feature; an edge can be defined as the boundary between two distincts regions, separated by the difference between gray levels. This difference may be due to the geometry of the scene, the content, the illumination and so many other factors. Edge detection is a delicate process in computer vision systems, specially for finding abrupt changes in image regions. The accuracy of this process is extremely significant for the overall performances of high level processing systems. Nowadays, most of applications use color images, since it provide more information than gray level ones. Thus, more detailed edge information are expected from edge detection [3]. An overwhelming evidence is that 90% of the edges are the same in gray and color images, which mean that 10% of the edges still left in gray scale images. These 10% remaining edges weaken the performances of detection and the consecutive processing step as, for example, edge based image segmentation or edge-based stereo matching [1]. In [11], Nevatia has proposed the first color edge detection by extending Hueckel operator. Little while, a wide range of

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approaches have been added to the literature. Practically all of them are adaptations of gray scale edge techniques to make them dealing with color images. There are generally, three classes of color extensions in the literature; output fusion methods, multi-dimensional gradient methods and vector methods. Apparently the output fusion is the most popular for it low coast implementation, since the goal is to fuse the results obtained by applying the detector to each component of the considered color space. Allegedly, there was no consistent work to compare highly correlated color space components and perceptual color space ones [10]. In this context, we propose to examine the performance of edge detection on different color components. For this purpose, we use canny edge detector on each component then we define the most relevant ones which will be considered as best candidates for a prospective combined space. The work is a quantitative comparative study that use latest robust statistical measures for edge quality assessment. We precisely intend to select the most relevants color components using quantitative evaluation models based on both, synthetic image (with single vertical line edge) and complex real world color images (from Berkley Segmentation Data Set) [8], with respective known ground truths. The paper is organized as follows. In section 1, we introduce some relevant points in the literature related to the edge detection problem. Then, we overview in section 2 the principal lineaments of the experimented color components. While we devote the section 3 to introduce our works by presenting the experimental setup including the adopted evaluation models and error measures, and also the considered color images with their respective ground truths. Section 4 contains the detailed results of the experiments. Finally, we conclude this study by summarizing the main observations presented trough out the paper.

2. COLOR SPACES

Color is the perceptual result of light in the visible region of the spectrum, it have also a physical aspect defined as the physical power (or radiance) and it is expressed in a spectral power distribution often in 31 components each representing a 10 nm band, however the actual technologies allowed exactly three types of color photoreceptor, so only three numerical components are necessary and sufficient to describe a color, providing an appropriate spectral weighting functions. Color images are sensed and reproduced based upon tristimulus values, which amplitude is proportional to radiance, but having spectral composition carefully chosen according to the principles of color science. According to the CIE system appearing in the CIE Publication 17.4 [13], hue is the attribute of a visual sensation according to which an area appears to be similar to one of the perceived colors, red, yellow, green and blue, or a combination of two of them, Saturation S is the color fullness of an area judged in proportion to its brightness component V. These definitions composed the first known color spaces (RGB and HSV). As formerly explained in the CIE Publication 15.2 [12], the YIQ color space uses a luma-chrominance encoding system invented in 1938 by Georges Valensi where the luma component Y represent the original monochrome signal and chrominance I and Q provides color information. While the YCbCr, is formed by a luminance component Y in addition to the blue and red differences Cb and Cr. Clearly, the color space literature contains a wide range of models which are generally placed into two categories: the highly correlated color spaces and perceptual ones. An actual important feature of the human color perception system is the color constancy. This concept is quite powerful in the field of color vision since it make, the colors perception of an object, remaining well-nigh constant under unstable conditions of illumination. Indeed many interesting achievements based on color constancy were recently published, perhaps the most convincing ones are the achievements done by Gevers et al. [5], where a numerous edge operators were adapted to color image basing on the color constancy concept.

3. METHODOLOGY

Throughout the development of the current study, our main goal is to find the best suited color space for edge detection. We intend to explore some perceptual color components, by computing the projection of a color image on them, then applying a reference operator on each calculated color component, and finally compare the resulting edge maps in order to find the components that helps to retrieve more accurate edges than with regular tristimilus. We also add a noise factor in our experiments to proof the need of robust color model in edge detection process, since all non ideal cases are contaminated with at least additive gaussian noise. From this study, we expect to clarify a rigorous definition of the most relevant color components for edge detection. Hence we experiment one of the most popular edges detectors ”Canny” [2], on the components of eight different color spaces including the classic tristimulus (RGB, HSV, XYZ, YIQ, YCbCr, CMYK, Lab, Luv). We then expect to see meadow, the behavior of the experimented operator, by considering its results for each experimented component among progressive gaussian noise variances. The performances evaluations are first performed on synthetic image with known edges locations using Fram and Deutsch [4], then we use latest robust statistical measures to evaluate the quality of edges obtained on real world color images with known ground truth edges, both taken from the Berkley segmentation dataset BSDS300 [8]. An important point to clarify concerns the instances of pixels detected as edges dues to the illumination variation of the scene. This class of edges will be considered as false detections and tend to penalize the performance of detection. A such evaluation rule implies the annulation of any specific implication of the gamut constraint on the assessed performances.

Problem of scale non-uniformity

As specified by the literature, the classical tristimulus RGB is highly correlated, unlike the perceptual color spaces. Unexpectedly, ones we want to examine the behavior of the selected operator, on this complex color components, we face an annoying problem, precisely related to the uncorrelated and non-uniformly scaled values in the converted color components. Consequently, the calculation time taken by almost all the edge detectors specially the statistical based ones, increase widely, which slow considerably the overall edge detection process. Indeed most of the color spaces gives in some cases, negatives, normalized in $[0,1]$, and even infinite values. We introduce a solution to overcome this scale non-uniformity by transforming the images values scale given by each color model to the interval $[0,255]$. We actually perform this values shifting transformation using the following algorithm :

im = RGB2ColorSpace(RGB image)
for each Component : K≥ 1 **do**
  Min = min((im(:,:,K))
  Max = max(im(:,:,K))
  for pixel : px > 0 **do**
    im(px,k)=$\frac{im(px,k)-Min}{Max-Min}$*255
  end for
end for

Where,
RGB2ColorSpace : Is the function that convert from the regular RGB color space to the targeted color space.
K: Is the index of each component of the current color space.
Min: Is the minimum intensity value of each component.
Max:Is the maximum intensity value of each component.
px: Is the location of each pixel in each component.

The experiments proved the importance of this transformation in overcoming the scale non uniformity problem by making the edge detection process faster for any color space.

4. Experimental Setup

Since our major need is to investigate the best suited color components to edge detection, we intend to experiment each component of the following color spaces RGB, HSV, XYZ, YIQ, YCbCr, CMYK, Lab and Luv using Canny operator [2]. We next discuss some important points of the experimental setup, starting by the selection of canny input parameters, followed by a brief presentation of experiments:

- Quantitative evaluation based on synthetic image containing a single vertical edge considered as ground truth (Fram and Deutsch).

- Quantitative evaluation based on robust statistical error measures (EM) using the hall set of color images in the BSDS300 [8]. This evaluation is completely based on the work and observations of Molina et al. [7].

The selection of Canny input parameters is a critical step in this performance evaluation. Indeed the initial 64 Canny's parameters were all combinations of sigma, low, and high, where **sigma** $\in$ **0.60, 1.20, 1.80, 2.40, low** $\in$ **0.20, 0.30, 0.40, 0.50, and high** $\in$ **0.60, 0.70, 0.80, 0.90;**. Naturally, the quality of extracted edge depends intrinsically on the selection of the optimal Canny's input parameters, which is not an easy task in our work case. Since each component instance from each experimented image imply it's own optimal Canny's parameters. All the more, the progressive gaussian noise contaminating the images used in the second experiment, make the parameter's selection process more complex. Fortunately Koren et al. [6] provided a robust solution for automatic selection of edge detector parameters based on an hybridization of Otsu's algorithm [14] and an adequate statistical theory.
An other unsettling problem is the randomness of the noise values generated for each single experiment. Many works overlook this problem by considering it as an implementation issue. In our work we choose to overcome it by executing the experiments process 24 times for each component. Then, we resume the results for each component, as the average of the 24 values for each considered measure.

4.1. Experiment 1: Evaluation with Synthetic model (Fram and Deutsch)

The first experiment consists into measuring the quantitative performance obtained by canny, basing on the P_1 and P_2 Fram and Deutsch parameters [4]. In fact, these two parameters are perhaps the first attempt to quantitatively resume the information on the quality of an edge map knowing it's ground truth. In this experiment part, we use as model a synthetic image with known both edge region R_e and edge zone Z_e with respective known sizes $R_e : (w_2 = 210, w_1 = 31)$ and $Z_e : (w_2^e = w_2 = 210, w_1^e = 4)$. But this model is affected by additive gaussian noise, the following figures show the synthetic model described above:

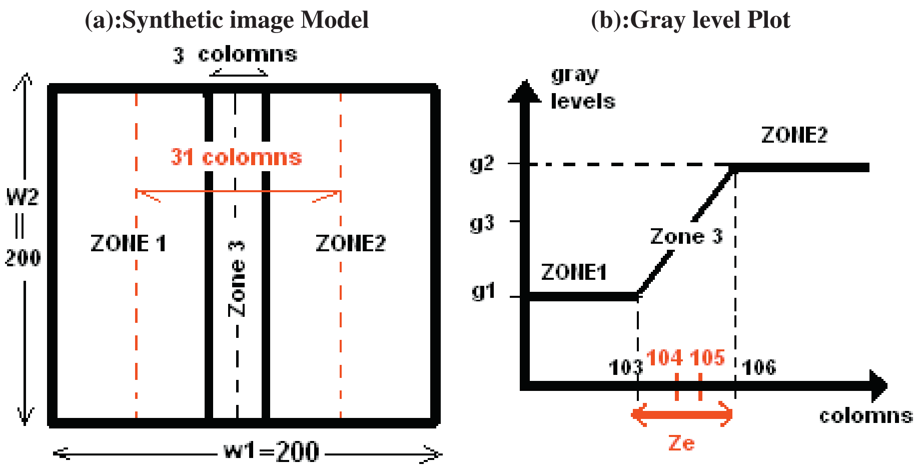

Fig. 1: Evaluation Model based synthetic image(a) and the corresponding gray levels plot (b), as described by Fram and Deutsch [4]

Note that this synthetic image have 3 components with values between $[0, 255]$ defined on the classic color space RGB.
In order to compare the edge detection performance on each component of each experimented color space, we used a synthetic image with both known edge region R_e fixed to 31 columns and edge zone Z_e fixed to 4 columns. However, we preferred a quantitative referenced evaluation based on Fram and Deutsch [4] measures P_1 and P_2 defined as follows:
Let the standard binary plane for edge detector output contain w_1 columns and w_2 rows. Let the "edge region" contain W_1^e columns and W_2^e rows. In this work, we consider that $W_2^e = w_2$. Let the number of edge pixels in the edge region R_e be n^e and the number of edge pixels outside the edge region be n^0. Note that while the n^e internal edge pixels are derivable from either signal only, noise only, or both signal and noise. The n^0 external edge pixels can only come from the noise in accordance with the quantitative model described by Fram and Deutsch. So, for the edge zone Z_e in

the extracted edge map the parameter P_1 is defined by:

$$P_1 = \frac{n^e_{sig}}{n^e_{sig} + (n^e_{noise} + n^0)(\frac{w_1^{stan}}{w_1})} \qquad where, \qquad n^e_{sig} = \frac{n^e - n^e_{noise}}{1 - \frac{n^e_{noise}}{w_1^e w_2}} \quad and \quad n^e_{noise} = n^0 \frac{w_1^e}{w_1 - w_1^e}$$

Where w_1^{stan} is the standard number of columns to which the noise edge pixels are normalized. It was set equal to 31. If n_r is the number of rows of the edge region which are "covered", then, parameter P2 is defined by:

$$P_2 = \frac{\frac{n_r}{w_2} - \{1 - [1 - \frac{n^e_{noise}}{w_1^e w_2}]^{w_1^e}\}}{[1 - \frac{n^e_{noise}}{w_1^e w_2}]^{w_1^e}}$$

Note that according to original Fram and Deutsch [4], the described two parameters have the following independent properties:

(a) should the edge pixels on the binary plane be distributed randomly with constant probability, the most probable values of both P_1 and P_2 are 0.

(b) should all the edge pixels of the binary plane fall within the edge region, then $P_1 = 1$.

(c) should every row of the edge be "covered," then $P_2 = 1$.

4.2. Experiment 2: Statistical Error Measures based Evaluation on BSDS300

Inadvertently an unsettling truth is claimed by scientific community which consider a such kind of evaluation (based on synthetic image) is not sufficient. In fact, since the synthetic images are ideal cases and do not fairly reproduce the chain of random perturbations which affect the overall energy in a real world image.
The second experiment is an attempt to give a powerful proof to the initial observations, discussed further down in the results section. We evaluate the quality of the extracted edges using a robust statistical error measures (EM's) appropriately selected on the light of Molina et al. observations [7]. Once we model the edge detection as a classification problem, it come that, for binary calculated edge map, the classification is binary. The comparison between this candidate edges with a fixed ground truth, imply that each pixel in the computed edge map can be classified into four different categories directly calculated from the confusion matrix. Inconveniently, these statistical measures fail to verify some constraints [7]. A simple alternative is to combine them in two or even one measure [16], true positive rate (TPR) and false positive rate (FPR):

$$TPR = \frac{TP}{TP + FN} \qquad FPR = \frac{FP}{FP + TN}$$

Venkatesh et al. uses the scalar coefficient $\Phi(E_{gt}, E_c)$ [15]:

$$\Phi(E_{gt}, E_c) = \frac{TP}{TP + FN} * \frac{TN}{TN + FP}$$

Martin et al. employs the F_α measure based on Precision-Recall **(PR)** concept [9]:

$$F_\alpha(E_{gt}, E_c) = \frac{P_{REC} * TPR}{\alpha * TPR + (1 - \alpha) * P_{REC}}$$

$$P_{Rec} = \frac{TP}{TP + FP} \quad \text{is the Precision Recall.}$$

Where $\alpha \in [0, 1]$ is a weighting parameter for the relative importance of the precision and recall evaluations. Lopez-Molina et al. [7], uses all the existing measures and defines a robust concept of error measure:

$$\Phi^*(E_{gt}, E_c) = 1 - \Phi(E_{gt}, E_c) \qquad and \qquad F^*_\alpha(E_{gt}, E_c) = 1 - F_\alpha(E_{gt}, E_c)$$

Also according to Lopez-Molina et al. [7] : "...All the options in the literature have flaws or biases that might be beneficial for the edge detection methods fitting their characteristics, which severely compromises the objectivity of any comparison." [7]. A direct solution to this problem can be provided by simply combining the results given by different measures. In this experiments part, we compute the measures TP, FN, Φ^*, $F^*_{\alpha=0.5}$, for each candidate edge map, obtained from each experimented component of each color image, after progressively contaminating the original image by additive gaussian noise with variance $\sigma^2_{noise} \in [0,60]$.

4.3. Ground Truth Solutions

The construction of ground truth solutions is not an obvious task. Many authors uses as optimal solution, the edge maps obtained by other techniques, assuming their perfectness. Arbelaez et al. published the Berkeley Segmentation Data Set and Benchmarks 500 (BSDS500), which is an extension of the BSDS300 [8], where the original 300 images used for training and validation, are added to 200 fresh images for testing. We actually consider the set of sixty nine color images in the original BSDS300 with theirs respective ground truths. Note that all used images are equally sized (321×481).

5. Results and Discussion

5.1. Results of Experiment 1

The first experiment is a quantitative evaluation performed on synthetic image with a single vertical edge.

Components	P_1	P_2
Red (R)	**0.8089**	**0.9752**
Green (G)	**0.7734**	**0.9707**
Blue (B)	**0.7780**	**0.9626**
Luma (Y) $\in$ YIQ	**0.9858**	**0.9888**
Luminance (Y) $\in$ YCbCr	**0.9858**	**0.9888**
Brightness (V) $\in$ HSV	**0.9268**	**0.9871**

Table 1: P_1 and P_2 values for Red, Green, Blue, Luma Y^{YIQ}, luminanceY^{YCbCr} and Brightness V^{HSV} components

The table 1 shows the resulting P_1 and P_2 values for canny operator, using the optimal set of three parameters, computed automatically as discussed before. Note that we present only the values of the interesting color components.

Initial Observations

Forthwith, the initial observations come out, according to the resulting P_1 and P_2 measures given above, we can clearly express the following initial observation:

1) In presence of additive gaussian noise, Canny operator referring to it's results on RGB color space, increase it's robustness toward noise whenever it's applied on **Y**, **Y**,**V** maps from respective color spaces **YIQ**, **YCbCr**, **HSV**. Indeed the informations on luma, luminance and brightness gives accurate edge details and refine the results of edge operator.

According to this initial observations, we can temporary assume the improvement of edge maps when the process is applied to the combination of the**Y**, **Y**, **V** maps from respective color spaces **YIQ**, **YCbCr**, **HSV**, instead of the regular tristimulus.

5.2. Results of Experiment 2

The second experiment is also a quantitative evaluation, but unlike the first one, only real world images are used. Also the performance are evaluated using robust error measures, in order to make the study more subjective and sturdy. Note that all experiments are done using canny operator with the optimal set of three parameters, computed

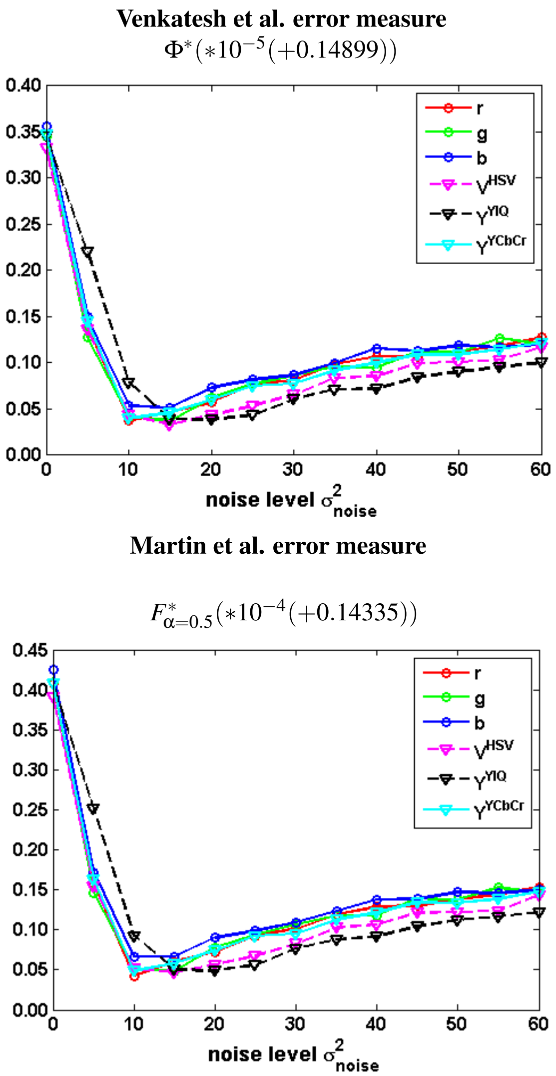

Fig. 2: Evolution of statistical error measures Φ^* and $F_{\alpha=0.5}$ among the progressive additive gaussian noise variances $\sigma_n^2 \in [0,60]$

automatically as discussed above.

Discussion

Figure 2 shows the evolution curves of Venkatesh and Rosin error measure Φ^* and Martin et al. error measure $F_{\alpha=0.5}$. All these measures has been computed among the progressive noise variances $\sigma_n^2 \in [0,60]$ for each experimented color component. From these resulting observations we first note an improvements in retrieving the 10% edges left (not detected in intensity images), when the detector is applied on luma, luminance and brightness. All the more, these three color components offer more robustness to the detector. Naturally, the idea behind combining these three components in one resulting color space become much more evident. Figure 3 illustrates an example for visual quality comparison between edge maps obtained using RGB and YYV. Inshort it's now evident that the combination of color components YYV result into highly accurate detection of edges and preserves shapes details.

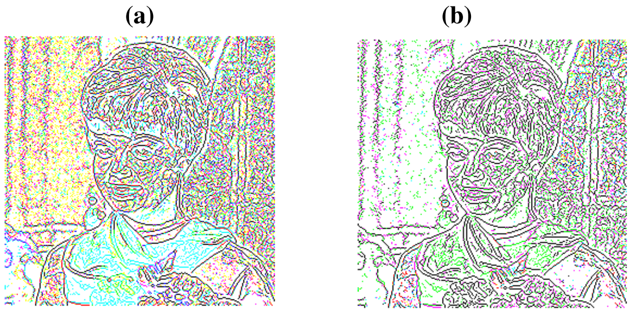

Fig. 3: (a): Edges obtained using RGB color space. (b): Resulting edge map using YYV color space

6. CONCLUSION

This study attempt to find the best suited color space for edge detection. The results of experiments demonstrate the increasing of Canny robustness towards gaussian noise. Also, we show its "covery" of the right edge pixels when applied to perceptual color components, rather than the regular RGB. As stated in this work, the color edge information is accurately collected in perceptual color components. The current paper, as a preliminary study, demonstrates effectively that more complex forms of color spaces can help to retrieve more accurate color edge information. Further work will concern the link between edge detection performances and color vision features like color constancy. Thereby, we hope that more complex perceptual color spaces can improve the edge detection process by insuring a better retrieving of the color edge information.

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